An Investigation into the Arrival Times of Campus Loop - Blue Buses in NTU using YOLOv5 and Gaussian Mixtures for Data Collection and Processing

ABSTRACT

This study focuses on the arrival times of the Blue Campus Loop in NTU, evaluating criteria such as average waiting times, seasonality, trend and frequency of bus bunching over a period of one teaching week. The process of data collection was automated, and a data pipeline was established using the YOLOv5 model and Gaussian Mixture clustering algorithms. The average waiting time for the blue campus loop buses was observed to be at an acceptable 7 minutes and 40 seconds. However, we observed a high degree of bus bunching, especially during the busy hours at around 2 pm. The bus arrival frequency did not remain the same through the observed days. Rather, it loosely rose around 4pm and then started to gradually drop in the evenings at around 6 pm. Based on our results, we propose that the most effective strategy to improve satisfaction with the NTU shuttle bus system would be to avoid buses plying close to each other. We hope that our study offers insights into the performance of the shuttle bus system in NTU and can serve as a benchmark study for future research.

1. INTRODUCTION

Public transportation is an integral part of Singapore. In the year 2020, an average of about 5 million passengers used some form of Public Transportation on a given day (LTA, 2020). About 60% of Singaporeans use the Mass Rapid Transit (MRT) for daily commute (Ibrahim, 2003). Thus, public transportation is an important aspect of everyday commute for people from all walks of life (Ong et al., 2009). This fact also holds true in the context of Nanyang Technological University (NTU)'s campus. Public Transportation in NTU plays a crucial part in students' journeys to and from their schools. Aside from the public bus services that rally to school from the nearby bus interchange of Boon Lay, NTU boasts of its own bus service as well.

1.1 SHUTTLE BUS SERVICES IN NTU

NTU currently has 3 shuttle bus services with express loops for 2 of the main services. The Campus Loop Blue and Campus Loop Red serve the entire perimeter of the NTU campus plying in opposite directions. There is also the Campus Rider Green which serves between the Pioneer MRT station and Tan Chin Tuan lecture theatre. On the weekends and public holidays this bus extends its services to cover the entire outer perimeter of NTU and is renamed as Campus Weekend Rider Brown. Additionally, there is a Campus Loop Yellow bus service that plies from Tan Chin Tuan Lecture Theatre to the Faculty Housing. However, since the Yellow bus service is rarely used by the students of NTU we have decided to omit it from our observations (Soh et al., 2011).

1.2 BUS STOPS COVERED BY THE SHUTTLE BUS SERVICES

The two main services; Campus Loop Blue and Red, ply between the different dormitories and the main buildings of NTU. The dormitories covered by the two services are Hall 2, 3, 4, 6, 8, 10, 11, 14, 15, Nanyang Crescent Hall and Nanyang Heights. The school buildings covered by the services are Lee Wee Nam Library, NIE, Yunnan Garden, School of Physical Mathematics and Sciences, Wee Kim Wee School of Communications and School of Civil and Environmental Engineering. As for the Campus Rider - Green, it serves from Pioneer MRT Station to Tan Chin Tuan Lecture Theatre and then back to Pioneer MRT Station (Soh et al., 2011).

1.3 THE PROBLEMS FACED BY STUDENTS WITH THE CURRENT BUS SYSTEM

In 2011, NTU students reported issues with the frequency of the shuttle bus services. About 34% of students were not satisfied by the peak frequency of the shuttle bus, whereas only 11% expressed satisfaction. The remaining 55% of the participants were indifferent to the peak frequency of the shuttle bus (Soh et al., 2011). Another potential issue for dissatisfaction with the bus system may be bus bunching. For the rest of the paper, we shall define bus bunching as the phenomena where two or more buses which were scheduled to be evenly spaced arrive at the same place at the same time. This occurs when at least one of the vehicles is unable to keep up in its schedule and therefore ends up in the same location as one or more other vehicles which are supposed to be ahead or behind it. Though the shuttle bus may perform its duty most of the time, there might be room for improvement and our findings could help future service providers in delivering better service to the students and faculty of NTU (Shahrin, 2020).

1.4 RESEARCH OBJECTIVES

With the aforementioned problems with the NTU shuttle buses in mind, we decided to investigate the frequency of the NTU shuttle bus services, narrowing our scope down to the Blue line as it covers major bus-stops used by most students and staff.

Our aim is to study the distribution of the Campus Loop - Blue bus throughout the week and also investigate the phenomenon of bus bunching. Weekends were not taken into account for the data collection as we believe the subsequent data collected could not be applied generally for the other days as the factors affecting the campus services may differ for the weekdays and the weekend. The results of our research would provide evidence pertaining to the efficiency of the current bus system and bring to light potential scheduling issues.

2. METHODOLOGY

This study involved four phases: phase one – the data collection phase where video footage was recorded over the course of a school week, phase two – the data processing phase where the recorded videos were processed to record the timestamps when a bus appeared, phase three – the data analysis phase where we segregated the data corresponding to the Campus Loop - Blue and a time series was generated and phase four - the statistical analysis where statistical tests were performed on the time series data.

2.1 DATA COLLECTION

The data collection was carried out with a camera/recording device in one of the dorm rooms in Hall 15. It was placed at an angle that looked over the Nanyang Crescent, a road which the Campus Loop Blue uses. The view of the road, as seen from the recorded video, is between the bus stops of Saraca Hall and Hall 14. Nanyang Crescent also has 2 more bus services using it along with the aforementioned NTU bus service – Campus Loop Red and SBS Transit Service 199. Campus Loop Red and 199 use the road close to the halls of Saraca, 15 and 14 (they move from right to left in the video) whereas the Campus Loop Blue is going in the opposite direction. With this setup, videos were recorded from Monday to Friday during Teaching Week 8 of academic year 2021 to 2022.

After leaving the setup running for a week, 5 video files of 6-8 hours each were obtained – ready to be processed. Each file was between 10 to 20 gigabytes in size and the frame rate for recorded videos was 30 frames per second.

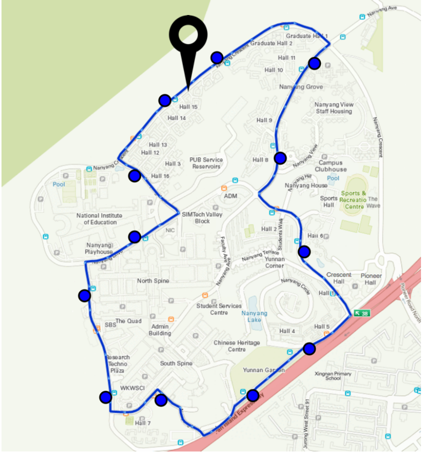

Fig 2.1.1 - Map of the route followed by the Campus Loop - Blue (Map Marker represents location where the videos were recorded)

Due to technical difficulties, the videos recorded were not of uniform length. The common interval of time present in all these video recordings was between 2:00 PM to 8:00 PM and only this portion of the recordings were used in further stages of the research. After the collection of unstructured data, the next step was to clean and process it.

2.2 DATA PROCESSING

After recording sufficient video footage over the week, the raw video files had to be processed before they could be used in any analysis. To generate a table that recorded the times when a bus passed through the frame of the video, we fed each video file into a deep learning model that performed object detection (Redmond et al.,2016). The aim being whenever a bus appeared in the view of the camera, the model would detect it by overlaying a bounding box and recording the time of appearance, creating a structured dataset in the process. A bounding box is a frame imposed on the objects detected by a deep learning model from the videos fed to it.

Fig 2.2.1 - Example of a bounding box overlaid by the YoloV5 model, object is a Campus Loop - Blue bus

The model selected was the Yolov5 model that had been pre-trained on the COCO dataset (Kim, 2019). To ensure that the model detected only buses that passed through the frame and not other vehicles, we discarded all categories other than the bus category from the pre-trained model. This allowed our model to recognize buses and not other vehicular types, tailoring it for our needs (Corovic et al., 2018).

However, this procedure did not guarantee that every vehicle detected by the model was a bus. To minimise the chances of the model misclassifying other vehicles as buses, like passing trucks or large cars, a probability threshold of 0.9 was set. This discarded wrong detections which further streamlined the existing tabular records and prevented any contamination of the data. After running the unstructured data through the Yolov5 model, a tabular record consisting of 5 columns was obtained.

x	y	w	h	frameNo
0.497222	0.375781	0.316667	0.0859375	6760
0.247222	0.367969	0.177778	0.0890625	7302
0.236111	0.366406	0.327778	0.0984375	7308
0.238889	0.367188	0.344444	0.096875	7309
0.248611	0.367188	0.341667	0.096875	7310
0.261111	0.367188	0.361111	0.09375	7311
0.268056	0.366406	0.347222	0.0984375	7312
0.276389	0.366406	0.352778	0.101562	7313
0.286111	0.366406	0.355556	0.101562	7314
0.302778	0.364844	0.355556	0.101562	7315
0.304167	0.364844	0.375	0.104687	7316
0.325	0.364062	0.35	0.103125	7317

Fig 2.2.2 - The first few rows of the tabular record

The columns were –

1. 'x' - the x-coordinate of the centre of the bounding box relative to the bottom-left corner (which is the origin), measured in pixels
2. 'y' - the y-coordinate of the centre of the bounding box relative to the bottom-left corner (which is the origin), measured in pixels
3. 'w' - the width of the bounding box, measured in pixels
4. 'h' - the height of the bounding box, measured in pixels
5. 'frameNo' - the frame of the video at which the object (bus, is this experiment) passed by the camera (this was later converted to timestamp)

The Yolov5 model processed each frame of the video footage in 0.01 seconds. With the frame rate of the videos being 30 frames per second, an hour consisted of 108,000 frames. Consequently, the model took 18 minutes for every hour of recorded footage and after around 9 hours of processing the videos, a cleaned dataset with the 5 columns mentioned above was generated, ready for further analysis.

2.3 DATA ANALYSIS

The aim of the data analysis process was to segregate the entries corresponding to the Campus Loop - Blue bus service, filtering out entries on other buses and anomalies like misclassified vehicles. The entries were segregated based on their size, particularly, the size of their bounding box. The entries were clustered based on the size of their bounding box (w,h) using the Gaussian Mixture clustering algorithm. The algorithm functioned by streaming the entries into groups, each group consisting of entries with similar bounding box sizes. Three clusters were obtained, consisting of,

1) Campus Loop - Red, Campus Loop - Blue and Single Decker SBS 199
2) Double Decker SBS 199
3) Misclassified Entries (Construction vehicles that were working on the road that week)

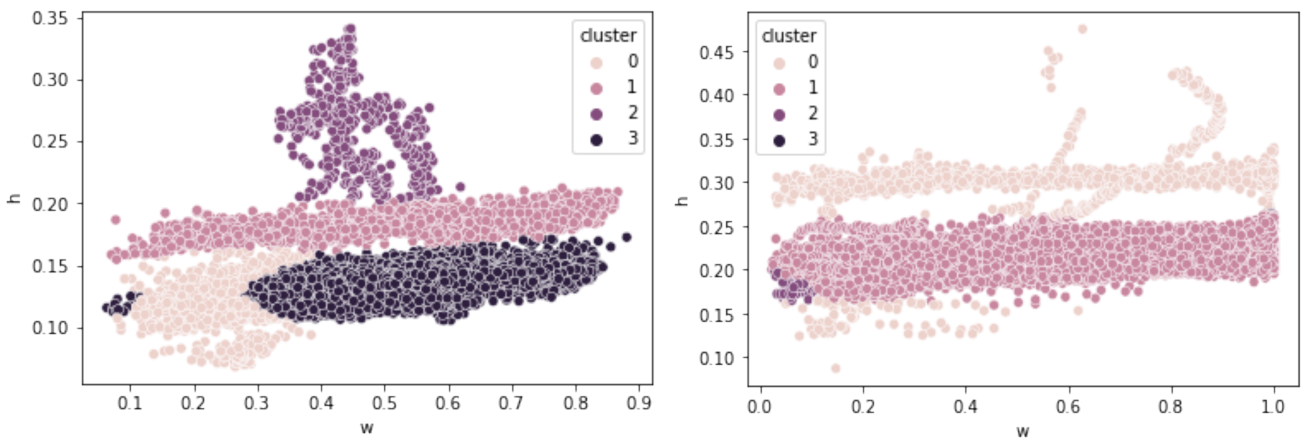

Fig 2.3.1. Clusters of different types of buses detected using Gaussian Mixture and AIC metric. (Monday and Tuesday scatter plots from left to right respectively)

Discarding clusters 2 and 3, the task of further partitioning the first cluster to extract the Campus Loop - Blue from the mixture of 3 entries was done leveraging the simple fact that the blue bus plied in the opposite direction. The Object Tracking capabilities of the YoloV5 model shown here, more specifically, the variation of the 'x' coordinate of each entry with time could determine the direction of motion of the bus.

Keeping in mind the fact that the 'x' coordinate was with reference to the bottom-left corner of the bounding box, If the 'x' coordinate value increases with time, it means that the object is moving from left to right from the point of view of the camera. However, if the 'x' coordinate value decreases with time, it means that the vehicle is moving from right to left from the point of view of the camera.

The simplest way to check this trend was by computing the Pearson Correlation Coefficient between the 'x' coordinate and the timestamp, a positive value implying the bus was travelling from left to right (Campus Loop - Blue) and a negative value implying the opposite (other buses, entries discarded). Thus, we were able to segregate the data of the Campus Loop - Blue cleanly and accurately.

As our videos were shot in 30 frames per second, if a bus took 2 seconds to pass through the video frame, there would be 60 entries corresponding to the position of the bounding box throughout its journey. To generate a time series, it was required to group these frames into one, corresponding to when a bus appeared in the video.

This was achieved by running the same Gaussian Mixtures clustering algorithm, grouping the entries based on their 'frameNo' and 'w' of the bounding box. The 'w' parameter was also used to handle the special case where two buses appeared in the frame of the video. Unlike the first time where we did not know the number of clusters beforehand, the number of clusters (number of Campus Loop – Blue buses in the video) was determined by studying the elbow plot using the AIC metric for clustering. This was done for each video separately, as the number of buses (clusters) might not have been the same.

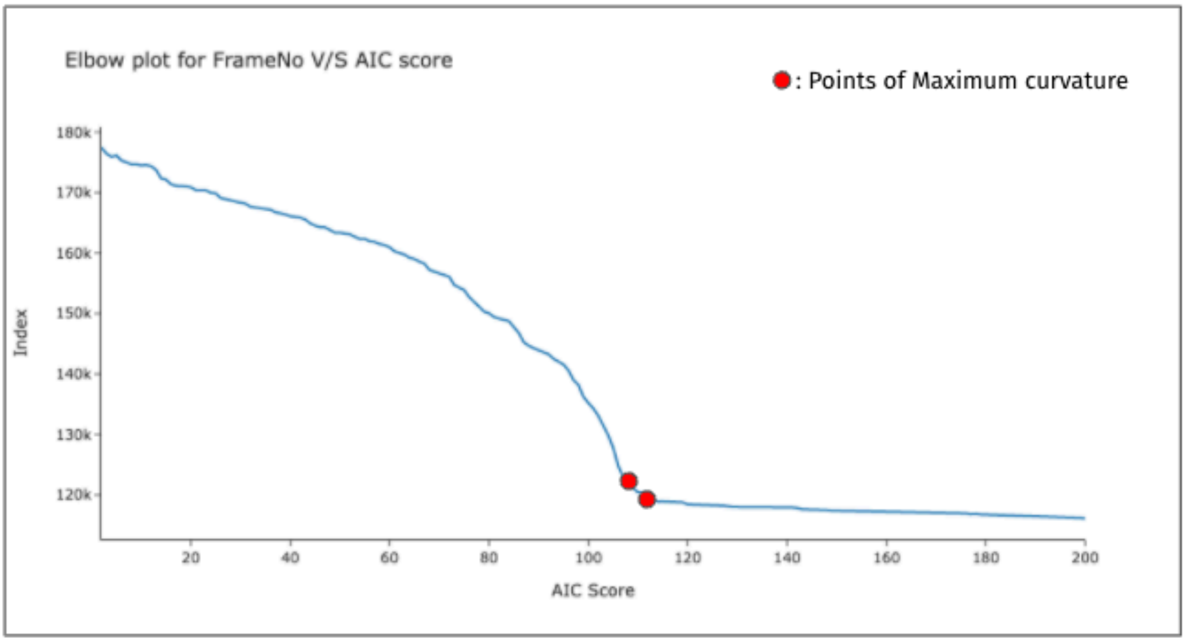

Fig 2.3.2. Elbow plot of AIC score V/S Number of clusters with points of maximum curvature.

Furthermore, the 'frameNo' column was converted to the timestamp using the fact that the videos were shot in 30 frames per second and that all videos began at 2:00 PM. Thus, a time series dataset was generated, ready for further statistical analysis.

2.4 STATISTICAL ANALYSIS

At this stage, we had time series data on the Campus Loop - Blue, for each day from Monday to Friday over a period of 6 hours (2:00 PM to 8:00 PM). A time series is a sequence of data records that occur in a consecutive order over a period of time. Thus, two statistical tests designed for time series analysis were performed with the aid of the statistical computing packages provided by the Python programming language (McKinney et al., 2011).

With the aim of studying the distribution of the buses for each day of the week, the trends of each dataset was analysed after transforming the data using the rolling mean. This would eliminate any noise in the data and the window size of the mean was determined by trial and error.

The seasonality of the time series was also studied using the technique of seasonal trend decomposition (McKinney et al., 2011), to detect any recurring patterns in the common interval of recording (2:00 PM to 8:00 PM). The length of this recurring pattern would help to approximately determine the time taken by the buses to complete their entire route.

Our secondary objective was to investigate the phenomenon of bus bunching. As this phenomenon did not require a common interval for analysis, the entire footage gathered over the week was utilised. This was carried out by analysing the timestamps and enumerating the instances where two or more buses were recorded within a threshold value. Such an instance would be a case of bus bunching. A threshold value of 2 minutes was chosen for the analysis.

3. RESULTS AND DISCUSSION

This study aimed to analyse the distribution of the Campus Loop - Blue and investigate the problem of bus bunching. Data was collected from Monday to Friday over the course of a school week. After processing and analysis, five time series datasets of the Campus Loop - Blue was obtained, one for each day. These datasets consisted of 30 - 40 records of these buses over the course of 6 hours. Plots of the Bus Frequency vs Timestamp for each dataset are given below.

After using the rolling mean to transform the data, the trends of the data, for each day, could be studied. The same general trend was observed for all days, most buses were recorded in the interval from 4:00 PM to 5:00 PM, after which their frequency steadily declines into the evening up till 8:00 PM. Taking the weighted average, it was determined from our data that one had to wait 7 minutes and 40 seconds on average for a Campus Loop - Blue bus to appear.

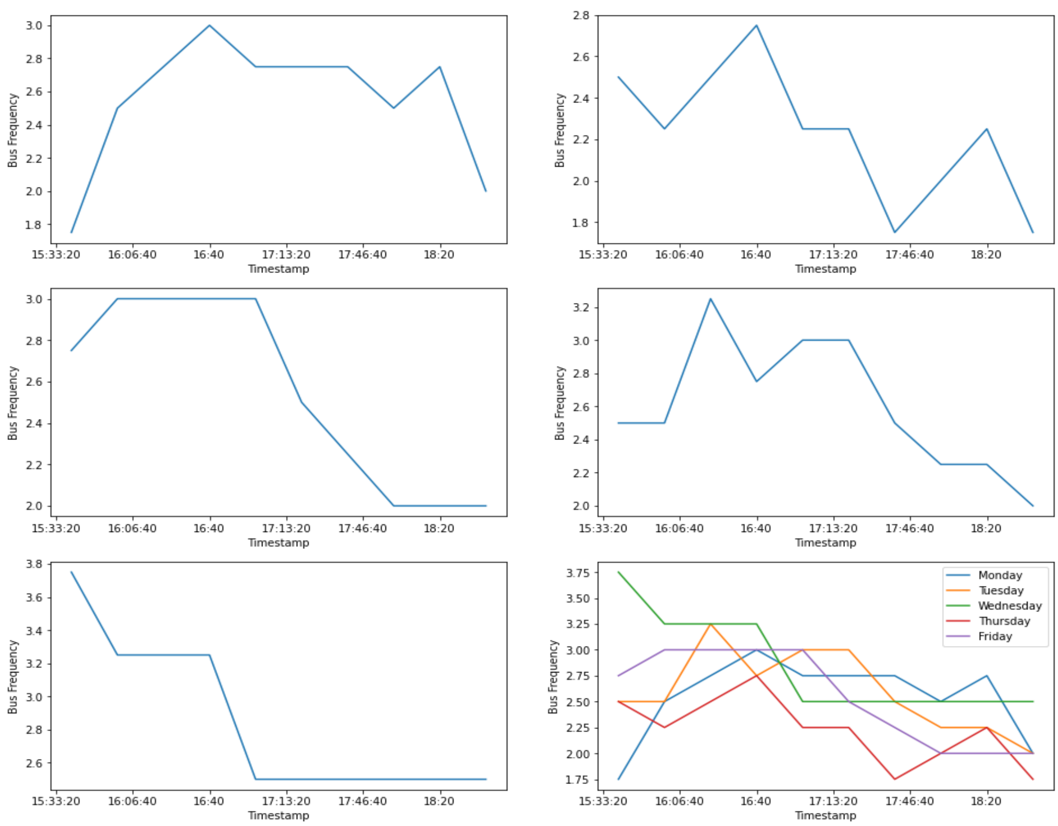

Fig 3.1 - Six Bus Frequency vs Timestamp plots, one for each day Monday to Friday and the sixth plot is all five together.

The seasonal trend decomposition applied on the data detected a recurring pattern in the daily data; the frequency of buses experienced the same changes every 25 minutes. This was expected as the route followed by Campus Loop - Blue buses was a loop, and it could be approximated that on average a bus takes 25 minutes to circle it. Coupled with the previous result about the average wait time, it was deduced that on average 3 (3.25 was the exact value which was rounded down) buses plied the loop together.

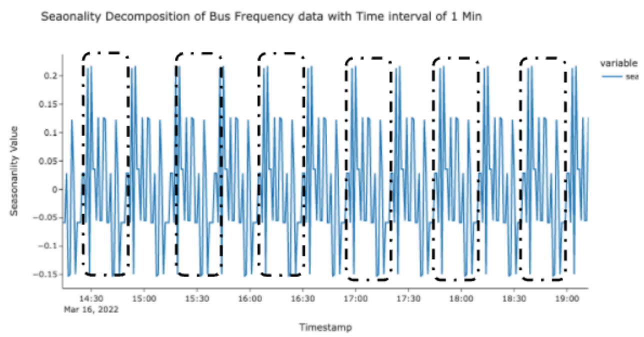

Fig 3.2 – Line plot of seasonality after Seasonal Trend Decomposition, the boxes highlight the repetition of pattern.

Finally, the investigation of the bunching of buses showed that this phenomenon occurs daily, with most instances of bunching occurring between 11:00 AM to 1:00 PM. Every instance of bunching detected had 2 Campus Loop - Blue buses appear in the frame within a duration of 2 minutes. This confirmed that bus bunching exists and identified a time where this problem is most prevalent.

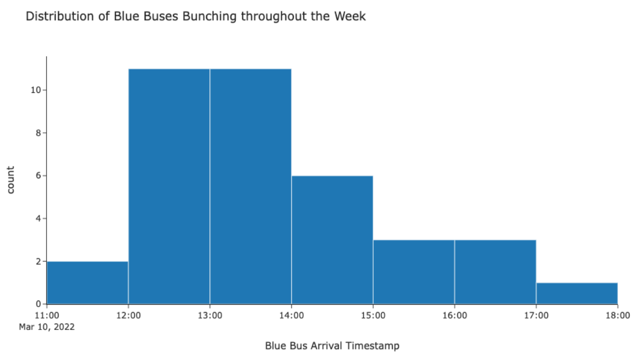

Fig 3.3 – Distribution of bus bunching frequency throughout the week

4. CONCLUSION

This study explored arrival times of the Blue Campus Loop in NTU, evaluating criteria such as average waiting times, seasonality, trend and frequency of bus bunching over a period of one teaching week. The process of data collection was automated, and a data pipeline was established using the YOLOv5 model and Gaussian Mixture clustering algorithms. Our results indicate a high degree of bus bunching, especially during the busy hours at around 4 pm. Additionally, the moderate average waiting time of 7 minutes and 40 seconds indicates that the students' dissatisfaction with the arrival times of shuttle buses may solely be due to the bunching of buses. To conclude, we propose that the most effective strategy to improve satisfaction with the NTU shuttle bus systems would be to avoid buses plying close to each other.

Our study was restricted by a small common window of time(2pm-8pm) for analysis because of hardware constraints, primarily, availability of a high-quality camera for long durations of time. Further research can be carried out with a larger sample size, possibly video data collected over weeks, to arrive at a more accurate estimate. Additionally, more parameters such as number of passengers on board the bus, weather conditions and the terminating stop of the bus could be considered for a more thorough analysis in the performance of the shuttle bus system in NTU.

5. REFERENCES

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